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Procedia CIRP 116 (2023) 480–485

www.elsevier.com/locate/procedia

30th CIRP Life Cycle Engineering Conference

Towards Early Damage Detection during the Disassembly of Threaded Fasteners using Machine Learning

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Abstract

At regular intervals, aircraft and their components, such as engines, are inspected following specified maintenance, repair and overhaul (MRO) guidelines. The modular design of the engines supports complete or partial disassembly for inspection of all relevant parts. The often used bolted joints are significantly altered by the harsh environmental conditions, severely increasing the disassembly effort usually carried out manually. Using tools like a ratchet or rotary impact wrenches, workers apply torque on the screw head to loosen the screw. If the loosening torque exceeds the material limits, screw heads are torn off, leaving the shaft in the base thread. This article presents a strategy to prevent disassembly damages through precise monitoring of the loosening torques and angle of rotation. Based on this data, a machine learning algorithm detects and predicts potential breakage, to allow adapted disassembly strategies to prevent complex rework. The algorithm will classify potential damage into different categories. Preliminary testing proved the applicability of machine learning toward aircraft disassembly.

Keywords: Disassembly; Threaded Fasteners; Damage Detection using Machine Learning;

1. Introduction

Aircraft engines are maintained, repaired and overhauled (MRO) in regular intervals to ensure safe operation. Alongside an inspection, they are disassembled to a certain stage depending on the specific maintenance task. Thus, components or assemblies that need to be inspected, repaired or replaced are accessed. To ensure that maintenance operations are carried out efficiently, modern turbofan engines have a modular design and are assembled by bolted joints. Likewise, system components such as cooling, electrical power generation, fuel components, hydraulic or pneumatic systems essential for the operation of the engine are connected to the engine with threaded fastenings.

Due to the harsh operating conditions of the engines, the assemblies, components and their fasteners change their properties, necessitating maintenance. On detailed examination of the threaded connections, the mentioned changes in properties lead to the joints altering. Consequently, the needed loosening torque is increased, and the fasteners can only be loosened with substantial effort. That, in turn, increases the risk of damaging the threaded fasteners during disassembly, for example, by tearing off the screw heads. As a result, the damaged fasteners have to be removed, leading to a significant additional effort due to potential further disassembly operations, extending maintenance intervals, and eventually financial loss, according to a maintenance service provider.

To prevent such damages and thus minimize the risk of further consequences, in the transfer project "Strategies for piezo-assisted disassembly of bolted joints" of the Collaborative Research Center (CRC) 871, "Regeneration of Complex Capital Goods" we are researching scientific methods and strategies for a gentle disassembly. In this article we present our research on the early detection of damaging the threaded fastener during the disassembly operation. By tracing the loosening torque and rotation angle, a machine learning algorithm will monitor the unscrewing process and forewarn of a possible tear-off of the screw head. Eventually, this prevents a destructive and thus ensures gentle disassembly of threaded connections.

This paper is structured as follows: In section 2, we will give a brief overview about related research. In section 3, we present the procedure and methods for our investigation, followed by the results in section 4. The paper is concluded with a discussion of the investigation in section 5, followed by an outlook for future research in section 6.

10.1016/j.procir.2023.02.081

2. Related Work

As introduced, the focus is the non-destructive disassembly of threaded fasteners, to minimize the risk of costly post-processing. Semi-destructive disassembly might also be considered, as long as the fastener is damaged and no post-processing of the base material, i.e. the aircraft engine, becomes necessary. When unscrewing threaded connections, the loosening torque is normally below the tightening torque and can be calculated according to the relevant literature [1]. However, screw locking mechanisms, such as mechanical, using i.e. toothed surfaces, or chemical, using adhesives, increase the loosening torque. Also, due to environmental influences, the aircraft's operation and overall wear, the condition of the threaded connections alter [2]. That change of the connection lead to a significant increase of the loosening torque. In previous work, for example, we have demonstrated that artificial aging of bolted joints increases the loosening torque up to 50 % [3].

While the deliberate torque-increasing effect of locking mechanisms is known, wear causes an unknown condition of the connection. Therefore, the disassembly of aircraft engines is predominantly characterized by manual work. By using specialized tools and treatment methods, the individual condition of the threaded connection can be addressed. However, during manual disassembly, damage such as stripped or torn screw heads occurs due to weakened screw materials and overdimensioned loosening torques. In contrast, automated disassembly operations are supervised by the control unit, monitoring the applied torque. In their work, Apley et al. (1998) categorized four unscrewing conditions and their torque and shaft rotation behavior [4]. Based on the time curves of the torque and the angle of rotation, they recognized a distinction between: (1) The disassembly tool properly engages the screw's head, and it is unscrewed, (2) the screwdriver engages the screw's head, but it slips on the head due to a damaged head, (3) due to an error in locating the screw, the screwdriver missed the screw's head and rotates without being engaged and (4) the screwdriver engages, but the applied torque is not sufficient to unscrew the screw. However, the detection and distinction of each category are still challenging and part of current research. While the first category (1) is the desired case for a non-destructive disassembly, latest research focuses on improving its detection as well as the detection of stripped non-detachable screws (2) [5] and optimized screw head localization and engagement strategies (3) [6]. Category (4) is easy to recognize since there is no rotation of the screwdriver, and the angle of rotation is, therefore, equal to 0 [4].

Considering closer the fourth category (4), unscrewing is performed with a maximum torque. A further increase in torque has not been investigated in this context, as the focus has been on non-destructive disassembly. Rather, this was investigated for the tightening of bolted joints. For example, the German engineering guideline VDI 2230 specified torque-controlled, angle-controlled and yield-controlled tightening [7, 8]. However, these guidelines were established for the safe operation of bolted joints by minimizing variations in preload force that can range between ±30−50 % [8]. Especially the yield-controlled tightening was detailed in these articles. With this procedure, the recorded torque increment is continuously divided by the increment of the angle of rotation by the assembly tool. By observing this difference quotient, an elastic or plastic deformation of the screw can be detected, and the tightening can be completed at the desired plastic deformation [7, 8].

For our investigation, we will use the known approaches and transfer them to the unscrewing task for disassembly. Therefore, this paper aims to determine the detection of unscrewing by the torque and angle of rotation diagrams. With manual disassembly, however, it is clear whether the tool engages the screw head or slips on a damaged head. In analogy to the results of Apley et al. (1998), the categories (2) and (3) can be omitted [4]. Furthermore, it will be analyzed whether new categories can be determined. These categories will consider the cases: 1. the screw can be turned and is in the elastic range, 2. the screw can be turned but is in the plastic range and 3. the screw head tears off. Since we are also mainly focusing on manual disassembly, the angle of rotation is often difficult or even impossible to record, due to the manual handling of the disassembly tools. We will therefore also look at the extent to which the angle of rotation can be excluded from the analysis. Considering that, we evaluate the applicability of supervised machine learning approaches, such as classification techniques [9].

3. Methods

This chapter describes the approach and method for our investigation. We present the test bench where the experiments were executed. The experiments consist of torsional tests, in which a loosening torque is applied to a tightened screw, and the resulting unscrewing process is measured. Next, the experimental setup is presented, followed by the description of the test planning.

3.1. Test bench

Figure 1 shows the test bench which was used for the torsional tests. The test bench consists of a drive motor with a gearbox connected to the sample mounting via a torque measuring shaft. The torque, rotational speed or angle can be adjusted through that motor. On the other side of the sample mounting is a brake motor with a gearbox, on which a counteracting load is set. The torsion test bench can apply and measure a test torque of up to 1.200 Nm and a rotational speed of up to 107 rpm. It is connected to a PC running LabVIEW to control the functionalities and store the measured values. The sampling rate of the recording is 200 Hz. The measuring PC logs the measured data of the actual torque, the angle of rotation and the set torque at each time stamp. The measurements are terminated manually after successful unscrewing or tearing off the screw head, resulting in a different number of measurement points for each run. That prevents the recording of measurements without any informative value.

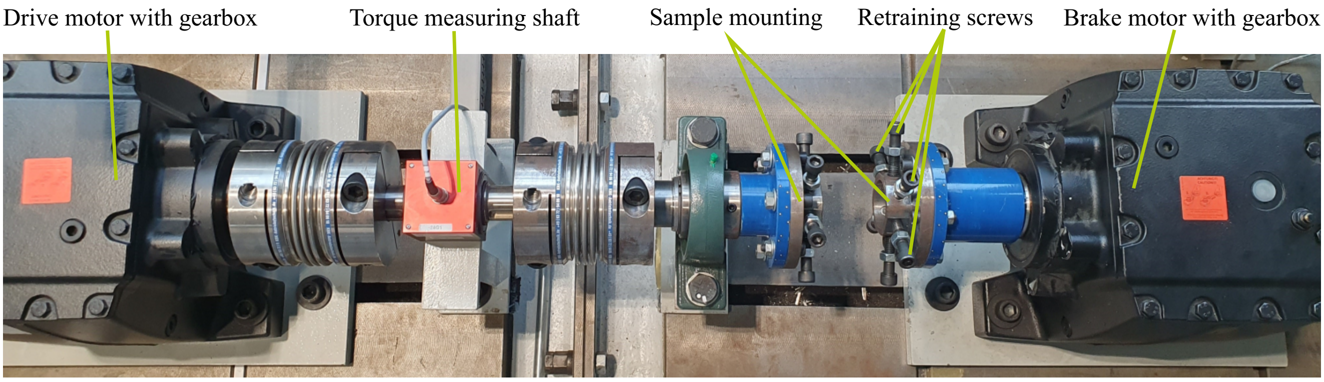

Fig. 1. Dynamic torsion test bench with a test torque of up to 1.200 Nm and a rotational speed of up to 107 rpm

3.2. Experimental Setup

To examine the screws on the torsion test bench, a sample mounting was manufactured in which the screws are inserted. Figure 2 shows the sample mount. It consists of two parts (Fig. 2a), in which the screw to be tested is mounted. The left side has a machined hexagon slot, in which the screw head is inserted and fixed using grub screws (Fig. 2b). The right side has a three-jawed thread, which clamps or locks the thread using the torsion test bench sample mount's retaining screws (Fig. 2c). Grub screws secure the jaws from falling out.

The experiments are performed using galvanized steel metric M8 hexagon head screws of strength class 8.8 with a length of 20 mm and regular threaded. For the experiment preparation, the M8 sample screws are screwed by the test bench into the three-jawed mount with a tightening torque equals 25 Nm. The test bench's retaining screws are then tightened to lock the thread in place. By varying the tightening torque of the retaining screws on the thread mount, a clamping effect is created on the thread of the screw. Thus, screw connections with different tightness are generated, replicating different altered threaded connections due to environmental influences. The following section will give a more detailed description of the resulting tightness (section 4). For the experimental studies, we tightened the retaining screws to 25 Nm, 50 Nm, 70 Nm and 100 Nm, respectively. Each experiment was conducted five times.

A maximum loosening torque is set on the test bench, with which the screws are untightened. Since the screw heads in previous attempts tore off with a torque of about 50.3±5.5 Nm, we set a maximum torque of 60 Nm, i.e. approximately 20 % up. Thereby we ensure that the screw head will tear off and the torque will not discontinue beforehand. With an increase of 1 Nm/s, the test bench then applies the set torque in the unscrewing direction.

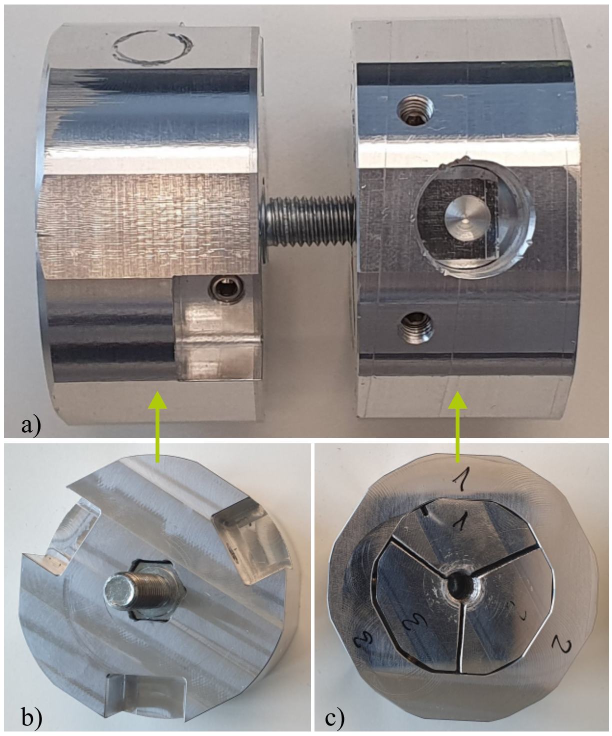

Fig. 2. Sample mounting: a) Side view, b) top view of the hexagon mount for the screw head, c) top view of the three-jaw mount for the thread

4. Results

As aforementioned, by tightening and clamping the screw in the three-jawed mount, we replicate altered screws due to environmental influences, i.e., the aircraft engine's operation. As the tightening torque of the retaining screws increased, the maximum loosening torque of the sample screws also increased. Looking at all the study's results in general, we observed that all five runs for each 25 Nm and 50 Nm were elastic unscrewed. However, one of the five screw heads was torn off when tightening with 70 Nm. In all experiments with 100 Nm, the screw heads were torn off without any recognizable damage. For a more in-depth investigation, we examine in excerpts of our experiments plotted graphs of the torque and angle of rotation curves, which will be analyzed in more detail in the following. We present the comparison of elastic and plastic unscrewing behavior. Then, a detailed examination of the gradients is presented, allowing a more in-depth examination. Lastly, the developing of an algorithm for pattern recognition and classification is presented. The curves shown are only an excerpt of all measurements. The other curves show similar behavior.

4.1. Torque - Angle of rotation curves

Figure 3 shows an exemplary plot of the recorded measured values loosening the metric M8 sample screw with a tightening of the retaining screws of 25 Nm. As described in the previous section, the set torque grows with 1 Nm/s. At the beginning of the measurement, the tightening torque is still applied to the screw's head, shown by the negative values of the recorded actual values of the loosening torque. Only minimal movement can be detected from the measured value of the angle of rotation since the torque is first built up in the unscrewing direction. After a time of approx. 11 s, an increase in the tool's angle of rotation can be detected when the values for the loosening torque shift into the positive range and further increase. After a time of approx. 22.5 s, a sudden increase of the tool's angle of rotation can then be seen, while the torque drops off suddenly after the continuous ascent. At this point, the sample screw starts to be unscrewed. The unscrewing torque is then significantly lower than the maximum loosening torque but still quantifiable due to the clamping of the thread and the resulting increased friction during the elastic unscrewing operation.

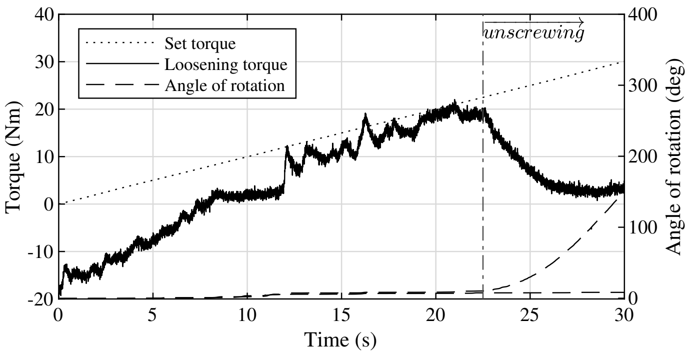

Fig. 3. Curve of the measured values for unscrewing at a tightening torque of the retainer screws of 25 Nm. Dotted line represents the set loosening torque with an increase of 1 Nm/s; solid line represents the actual values for the loosening torque; dashed line represents the tool's angle of rotation

In comparison, Figure 4 shows an exemplary plot with a tightening of the retaining screws of 70 Nm. Due to the tighter clamping of the thread, the maximum loosening torque was considerably higher. The measured peak loosening torque before the unscrewing movement occurred was 50.9 Nm, lying in the range of the previously determined maximum loosening torque at which the screw heads likely tore off. Yet, the screw was unscrewed without any noticeable plastic deformation, as the curve is similar to Figure 3. Also, the tool's angle of rotation curve is similar to Figure 3. However, more absolute rotational movement is necessary, to build up the torque. When the unscrewing movement begins, the rotational increases and follows a similar behavior, as the loosening torque drops.

When tightening the retainer screws with more than 70 Nm, the sample screw's head tore off. Figure 5 shows the curves for a tightening torque of the retainer screws of 100 Nm. In the curve of the loosening torque, there is initially a steady ascent, as before. The measured peak value for the loosening torque in this exemplary investigation was 52.0 Nm. However, in the

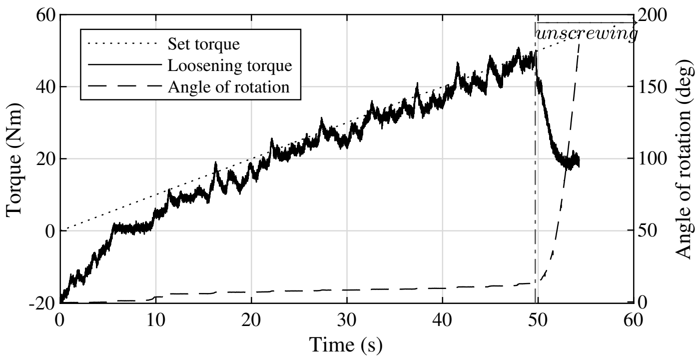

Fig. 4. Curve of the measured values for unscrewing at a tightening torque of the retainer screws of 70 Nm.

further process, there is an apparent flattening in the range of about 50 Nm. In this region, we expect the plastic deformation to appear, but it was not measured further. Compared to the previous investigations, this state continues for about 10 s, between a time of approx. 50 to 60 s, until it slowly decreases until a time of 63 s when then the measured loosening torque drops abruptly. The tearing off of the screw head was clearly audible. From here on, the head rotates loosely, which can be seen in the torque curve near 0 Nm, before the recording of the measurement was closed.

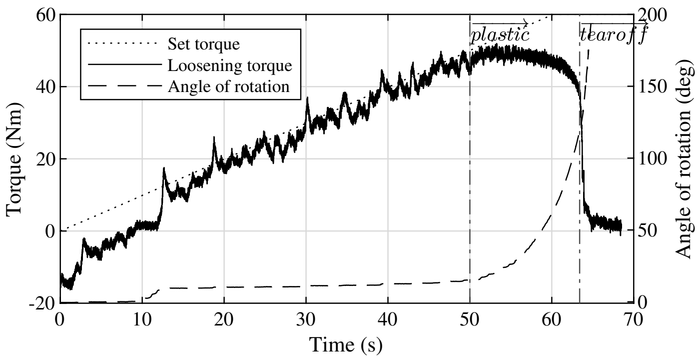

Fig. 5. Curve of the measured values for unscrewing with subsequent tearing off the screw head at a tightening torque of the retainer screws of 100 Nm.

4.2. Gradient curves

As seen in the graphs (Fig. 3, 4 and 5), the beginning and the moment of tearing off the screw head were distinguishable from the unscrewing of the screw. This has led to potential fluctuations in the results. For better visibility, e.g. manual monitoring, we filtered the noisy values for the loosening torque with the 1-D median function of MATLAB R2022a (1000th-order one-dimensional median filter). To further examine the behavior during unscrewing, we also calculated and plotted the gradient of the filtered actual loosening torque and the angle of rotation. Figures 6 and 7 show the curves for the filtered torque (a) and the corresponding gradient (b) for 70 Nm and 100 Nm, respectively.

As before, similarities and differences can be identified in the curves of the gradient of loosening torque and the angle of rotation: Up to the maximum release torque, a significant increase in the loosening torque with a slight increase in the angle of rotation can be identified. In the plots for 70 Nm (Fig. 6b), the loosening of the screw and the subsequent unscrewing can be recognized by a gradually decreasing torque right after a noticeable peak. This behavior indicated an elastic unscrewing.

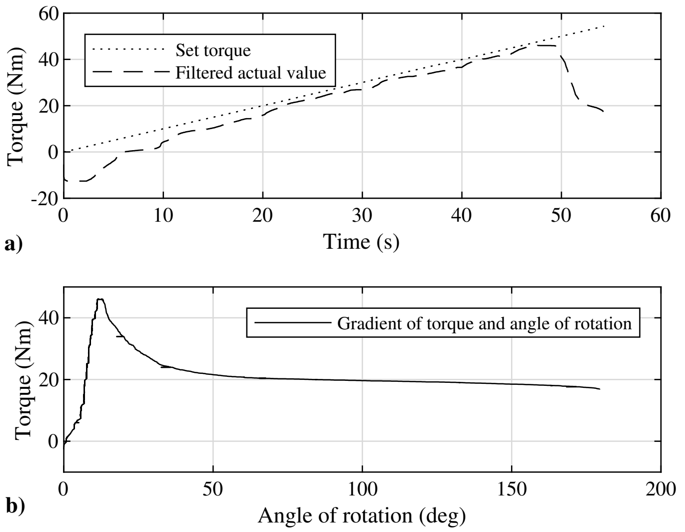

Fig. 6. Curve of the evaluated values of Figure 4. a): Dotted line represents the set torque with an increase of 1 Nm/s; dashed line represents the filtered values of the actual loosening torque. b): solid line represents the gradient of the filtered loosening torque and the angle of rotation

However, in the curve for 100 Nm (Fig. 7b), the gradient is apparent flattening, although a rotational movement occurs, seen by the increasing angle of rotation and a roughly constant and slightly decreasing applied torque. The slight decrease is followed by a significant drop of the torque. We also assume that the flattening of the gradient implied the beginning of plastic deformation of the screw, which subsequently led to necking and the subsequent tearing off of the screw head. Therefore, if a flattening gradient of the loosening torque and angle of rotation is observed, possible damage, such as the tearing off of the screw head, can be detected at an early stage. A flattening of the gradient over the progress of the disassembly operation with an apparent movement can indicate upcoming damage.

In summary, the gradient could detect at an early stage whether unscrewing or plastic deformation is occurring with subsequent tearing off of the screw head. This allows thresholds to be defined for the gradient. When the thresholds are exceeded, it can be determined whether unscrewing or plastic deformation will occur. While recording and monitoring of the angle of rotation are feasible for automated disassembly, they will be complex tasks in manual disassembly. Since, the worker exerts the tool's movement, no detailed data on the angle of rotation is available. However, the torque is measured. As seen in the graphs, the applied torque provides sufficient data to be adequate for a determination of the occurring unscrewing events.

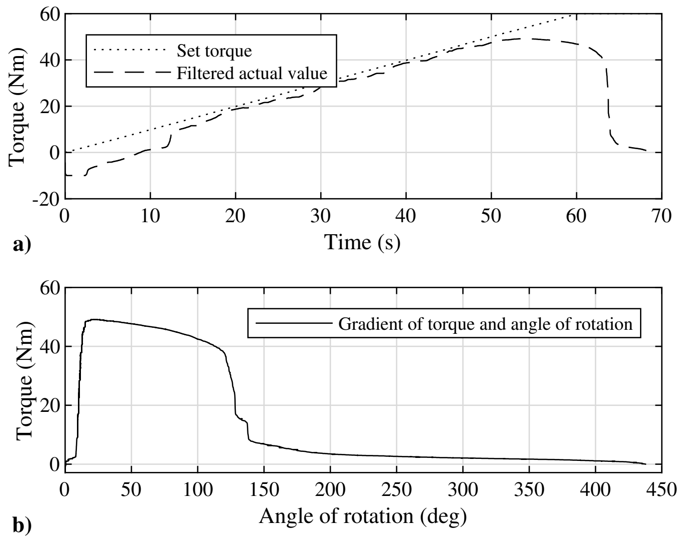

Fig. 7. Curve of the evaluated values of Figure 5.

4.3. *Classification using machine learning*

Manual monitoring of the torque and angle of rotation curves during the disassembly process already provides promising indicators for the early detection of a tear-off of the screw head. With the help of machine learning algorithms, we aim to support the detection process. MATLAB 2022a offers the function of a Classification Learner application. The application trains the data and proposes the best fitting algorithm for the input.

Before the classification, the feature exploring and extraction is necessary. That includes determining the unscrewing events on which the classification algorithm is to be trained [10]. We used the Signal Labeler application in MATLAB to manually define the regions in the unfiltered data, as in subsection 4.1, where the previously recognized events, elastic unscrewing, plastic deformation and tearing off the screw head, occurred. Then, the data was exported to the Classification Learner, trained to predict the events. The input data are the arrays containing the labeled excerpts of the loosening torque curves and the outputs are the corresponding events. By using the data recorded at 200 Hz, the proposed algorithm can better distinguish between sudden action of unscrewing or tearing off and slower plastic deformation. Entering our data of 26 extracted features, the Classification Learner will train the algorithm, followed by a 5-fold cross-validation. Thus, the application divides the data into five disjoint sets (fold). Four folds are used as training data, while the remaining fold (held-out fold) is used as validation data to train the model. That is done five times, each time using a different held-out fold. The accuracy is calculated for each iteration, while the average is the accuracy for the model. Thereby, we both prevent over- or underfitting. The algorithm recommended by the classification learner was the classification decision tree [11]. Figure 8 shows the confusion matrix for the validation of the Fine Tree classification with 19 out of 26 correctly assigned features.

However, the wear-heavy test procedure had a disadvantageous effect. High tension forces had to be applied to the

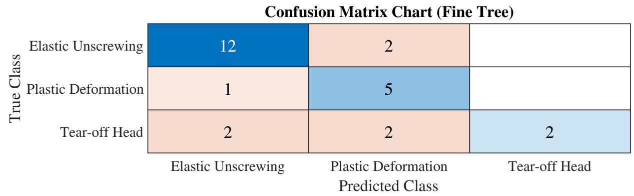

Fig. 8. Confusion matrix of the decision tree algorithm to classify the measured data

thread, which weakened the materials, especially for recording the screw tear-off cases. The results showed that further effort is required to complement the class for disassembly processes with damaged screws. Although the approach generally displays the intended result, the lack of the plastic deformation and tear-off screw head categories is evident. Also, the manual labeling of the data can lead to misidentifications. Further research and experimental investigation, significantly expanding on those categories, is essential. Then, live monitoring for early detection can be developed and integrated.

5. Discussion

In the evaluation of our tests, we were able to distinguish well between unscrewing and tearing off the screw head. As we introduced, we aimed to determine new categories and to detect upcoming damages during unscrewing. A more detailed analysis of the recorded curves for the torque, the angle of rotation and their gradient indicated different events for elastic unscrewing, plastic deformation and tearing off of the screw head. However, we could not detect any successful unscrewing process in which the sample screw was plastically deformed without tearing off the head. The clamping of the thread also damaged the sample mounting, so that it had to be reworked several times. This has led to potential fluctuations in the results. In further investigations, we are working on the extension of the experiments. That includes the optimization of the sample mounting, also to be able to record plastic unscrewing processes.

Instead of complex analysis and the learning of algorithms, a simple decision tree could also be used, which stops any disassembly process when exceeding a given maximum torque (in this case, approx. > 50.3 minus a safety value). But, important aspects would not be considered: On the one hand, fatigue behavior can weaken bolts and change torque limits. On the other hand, our investigations show that disassembly near the torque limits is feasible but requires monitoring. The supervision of the given maximum torque should be integrated to the monitoring developed from our work.

6. Outlook

An existing test environment was used for the investigation. It is primarily designed to test friction-welded shafts with diameters of up to 60 mm for torsional strength and dynamic endurance tests using high torques. The sample mount used for the bolts showed usability in the results but only limited durability due to its earliest design. In future work, we plan to design and build a test environment, with a better dimensioned range for the investigated M8 bolts. Thus less noisy measurements are achieved.

Also, we will examine the extent to which the e.g. aircraft engine's operation weakens the screws. For example, it reduces the strength of the screw and thus reduces the torque at which the screw head tears off. We will use artificial aging to replicate various operating scenarios, including examining the screws of used aircraft engines. In addition, in the case of real altered screw connections, e.g. rusted screws, an increased friction behavior also occurs in the head contact surface, which is not considered further in the case of the thread clamping, we used in our investigation. Therefore, an optimized mounting for the sample screws must be developed for further studies that adress both cases: thread friction and head contact surface friction. That will also allow the studies for machine learning to be extended.

Acknowledgements

We gratefully acknowledge financial support by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation), funding code: SFB 871/3, T16#.

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